Table 16 Summary of ML-based fault prediction

Ref.	ML Technique	Network (*location*)	Dataset	Features	Output (*training*)	Evaluation Settings	Evaluation Results
Hood et al. [193]	Supervised: · BN	Campus network	Data collected from router	Management information base (MIB) variables for following network functions · Interface group · IP group · UDP group	Predict network health	500 samples for each of 14 MIB variables of the 3 network functions	Predict approximately 8 min before fault occurrence
Kogeda et al. [248]	Supervised: · BN	Cellular network	Simulation with fault injection	·Power ·Multiplexer ·Cell ·Transmission	Faulty or not	4 nodes each with 3 states	Confidence level of 99.8%
Snow et al. [414]	Supervised: · NN (MLP)	Wireless network	Generated using discrete time event simulation	·Mean time to failure ·Mean time to restore ·Time Profile ·Run Time	Dependability of a network ·Survivability ·Availability ·Failed components ·Reportable outages	14 inputs, 10 and 5 nodes in the first and second hidden layer, respectively	Closely approximates reportable outages
Wang et al. [466]	Supervised: · DT (J4.8) · Rule learners (JRip) · SVM · BN · Ensemble	Wireless sensor network	Generated using sensor network testbed	·Received signal strength indication ·Send and forward buffer sizes ·Channel load assessment ·Forward and backward	Link quality estimation	10-fold cross validation was used with 5000 samples	Accuracy · 82% for J4.8 ·80% for JRip
Lu et al. [285]	Manifold learning: ·SHLLE	Distributed systems	Generated from a testbed of a distributed environment with a file transfer application	System performance ·interface group ·IP group ·TCP group ·UDP group	Prediction of network, CPU, and memory failures	Not provided	· Precision: 0.452 ·Recall: 0.456 · False positive rate: 0.152
Pellegrini et al. [355]	Different ML methods: ·Linear Regression · M5P · REP-Tree · LASSO · SVM · Least-Square SVM	Multi-tier e-commerce web application	Generated from a testbed of a virtual architecture	Different system performance	Remaining Time to Failure (RTTF)	Not provided	Soft mean absolute error · Linear regression: 137.600 · M5P: 79.182 · REP-Tree: 69.832 · LASSO as a Predictor: 405.187 · SVM: 132.668 · Least-Square SVM: 132.675
Wang et al. [469]	Supervised: · Double-exponential smoothing (DES) and SVM	Optical network	Real data collected from an optical network of a telecommunications operator	Indicators In Board Data: ·Input Optical Power · Laser Bias Current · Laser Temperature Offset · Output Optical Power · Environmental Temperature ·Unusable Time	Predicting equipment failure	10-fold cross-validation was used to test model accuracy	DES with SVM · Prediction accuracy: 95%
Kumar et al. [255]	Unsupervised: · DNN with Autoencoders	Cellular Network	Fault data from one of the national mobile operators of USA for a month	Historical data of fault occurrence and their inter-arrival times	Prediction of inter-arrival time of faults	10 neurons in the hidden layer	DNN with autoencoders · NRMSE: 0.122092 ·RMSE: 0.504425

Table 17 Summary of ML-based Fault Detection

Ref.	ML Technique	Network (*location*)	Dataset	Features	Output (*training*)	Evaluation Settings	Evaluation Results
Rao [382]	Statistical learning	Cellular network	Data collected from real cellular networks	Mobile user call load profile	Detect faults at ·Base station level ·Sector level ·Carrier level ·Channel level	Not provided	Bounded probability of false alarm
Baras et al. [37]	A combination of NN (radial basis functions)	Cellular network (X.25 protocol)	Simulation with OPNET	For each fault scenario ·Blocking of packets ·Queue sizes ·Packet throughput ·Utilization on links connecting subnetworks ·Packet end-to-end delays	Detect one of the fault scenarios ·Reduced switch capacity ·Increased packet generation rate of a certain application ·Disabled switch ·Disabled links	Varying number of hidden nodes between 175 and 230	Different rates of errors
Adda et al. [5]	Supervised: · *k*-Means ·FCM ·EM	IP network of a school campus	Obtained from a network with heavy and light traffic scenarios	12 variables of interface (IF) category collected through SNMP	Fault classes: · Normal traffic ·Link failure traffic ·Server crash ·Broadcast storm ·Protocol error	Not provided	Precision for heavy scenario in router dataset · *k*-Means = 40 · FCM = 85 · EM = 40
Moustapha and Selmic [324]	Supervised: · RNN	Wireless sensor network	Collected from a simulated sensor network	·Previous outputs of sensor nodes· Current and previous output samples of neighboring sensor nodes	Approximation of the output of the sensor node	8-10-1[a]	Constant error smaller than state-of-the-art
Hajji [178]	Unsupervised change detection method	Local area networks	Collected from a real network using remote monitoring agents	Baseline random variable	An alarm as soon as an anomaly occurs	Time to detect : · 50 s to 17 min	Accuracy: 100% · Low alarm rate: 0.12 alarms per hour
Hashmi et al. [181]	Supervised: · *k*-Means · FCM · SOM	Broadband service provider network	1 million NFL data points from 5 service regions	·Fault occurrence date ·Time of the day ·Geographical region ·Fault cause ·Resolution time	Identify the spatio-temporal patterns linked with high fault resolution times	SOM on a 15x15 network grid for 154 epochs	Sum of squared errors: ·*k*-Means = 2156788 · FCM = 2822823 · SOM = 1136

[a]Number of neurons at the input layer, hidden, and output layers, respectively

Table 18 Summary of ML-based fault localization

Ref.	ML Technique	Network	Dataset	Features	Output	Evaluation	
		(*location*)			(*training*)	Settings	Results
Chen et al. [91]	DT (C4.5)	Network systems	Snapshots of logs from eBay	A complete request trace ·Request type ·Request name ·Pool ·Host ·Version ·Status of each request	Different faulty elements	10 one hour snapshots with 14 faults in total	·Precision: 92% ·Recall: 93%
Ruiz et al. [393]	BN	Optical network	Synthetically generated time series	Quality of Transmission (QoT) parameters ·Received power ·Pre-forward error correction bit error rate (pre-FEC BER)	Detect one of the two fault scenarios ·Tight filtering ·Inter-channel interference	5,000 and 500 time series for training and testing, respectively	Accuracy: 99.2%
Khanafer et al. [237]	BN and EMD	Cellular network	Synthetically generated from a simulated and a real UMTS network	·Causes of faults ·Symptoms, i.e., alarms and KPIs	Identify the cuase of the fault	77 and 42 faulty cells for training and testing, respectively	Accuracy: 88.1%
Kiciman and Fox [241]	Supervised: · DT (ID3)	Three-tier enterprise applications	Generated using small testbed platform	Paths classified as normal or anomalous	Hardware and software components that are correlated with the failures	Three different DTs were evaluated	Correctly detect 89% to 96% of major failures
Johnsson et al. [225]	Unsupervised: discrete state-space particle filtering	IP network	Discrete event simulator	·Active network measurements ·Probabilistic inference ·Change detection	Probability mass function indicating the location of the faulty components	Operations per filter: $O(\|G\|)$, where $\|G\|$ is the number of edges in a graph G	Found the location of faults and performance degradations in real time
Barreto et al. [40]	Unsupervised: · Winner-Take-All (WTA) · Frequency-Sensitive Competitive Learning (FSCL) · SOM ·Neural-Gas algorithm (NGA)	Cellular network	Simulation study	State vectors representing the normal functioning of a network	State vector causing the abnormally	400 vectors were used for training and 100 vectors were used for testing	False alarm: · WTA: 12.43 · FSCL: 10.20 · SOM: 8.75 ·NGA: 9.50